Notes on Validation of Prognostics Algorithms

Diagnostics and Prognostics Group

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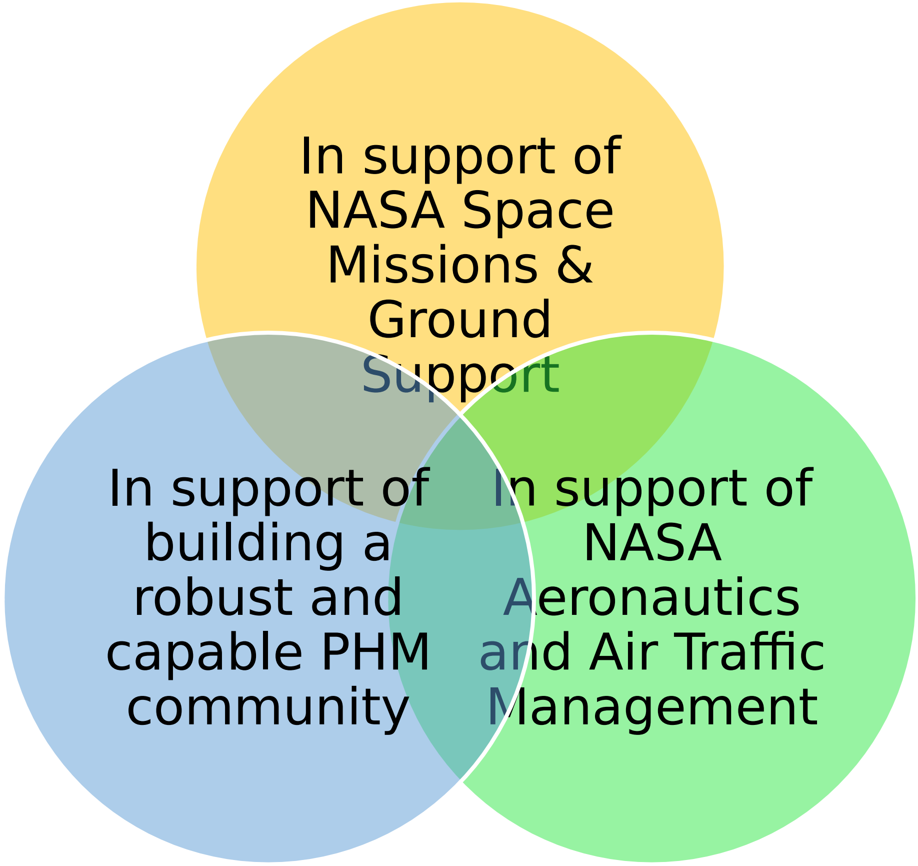
INTELLIGENT SYSTEMS DIVISION

Algorithm Design | Prototyping | Simulation | Benchmarking | Validation → Fault Detection | Diagnostics | Prognostics | Mitigation | Performance Metrics | Resilient Design

Research Areas

- Physics-based diagnostics and prognostics algorithms and models
- Data-driven diagnostics and prognostics algorithms
- Hybrid prognostics approaches/ Physics Informed Machine Learning (PIML)
- Uncertainty representation and management
- Resource-constrained prognostics
- Surrogate modeling
- Testbed development and automated testing for prognostics
- Human-machine interaction (HMI)
- Software Architectures for Prognostics
- Health-informed decision-making under uncertainty
- Verification and validation (V&V) of prognostics and health management (PHM) systems



Notes on Validation of Prognostic Technologies

The group did work on formal validation approaches in the past [4]:

- **α-λ Performance:** quantifies prediction quality by determining if the prediction falls within specified limits at times with respect to a performance measure.
- **Relative Accuracy:** Relative Accuracy (RA) is defined as a measure of error in RUL prediction relative to the actual RUL $r^*(i_\lambda)$ at a specific time index i_λ.
- Validation Techniques[8], and systems engineering processes[9]

Now, we do not generally have a standard approach that's used for every case, since our work is often exploratory (research). Instead, we validate to the degree necessary on a case-by-case basis, depending on the technology and scope of validation.

- Generally, validation is not seen as binary decision point, but rather a scale of validation (like TRLs) corresponding to confidence that we can have in a technology.
- Validation also has a specific scope. For example- validating a battery model for use on 18650s is very different than validating a battery model for all Lithium-Ion Batteries.
- Validating in laboratory environment is useful, but not a substitute for validation in a relevant operational environment.

Frequently Used Tools & Approaches

- Lab Testbeds
- Fault Emulation/Injection
- Operational Tests
- Input - predicted output correlation analysis
- True output – predicted output correlation analysis
- Confidence interval at specific confidence levels
- Specific Prognostics Metrics: Alpha/Lambda, Prognostics Horizon, etc.

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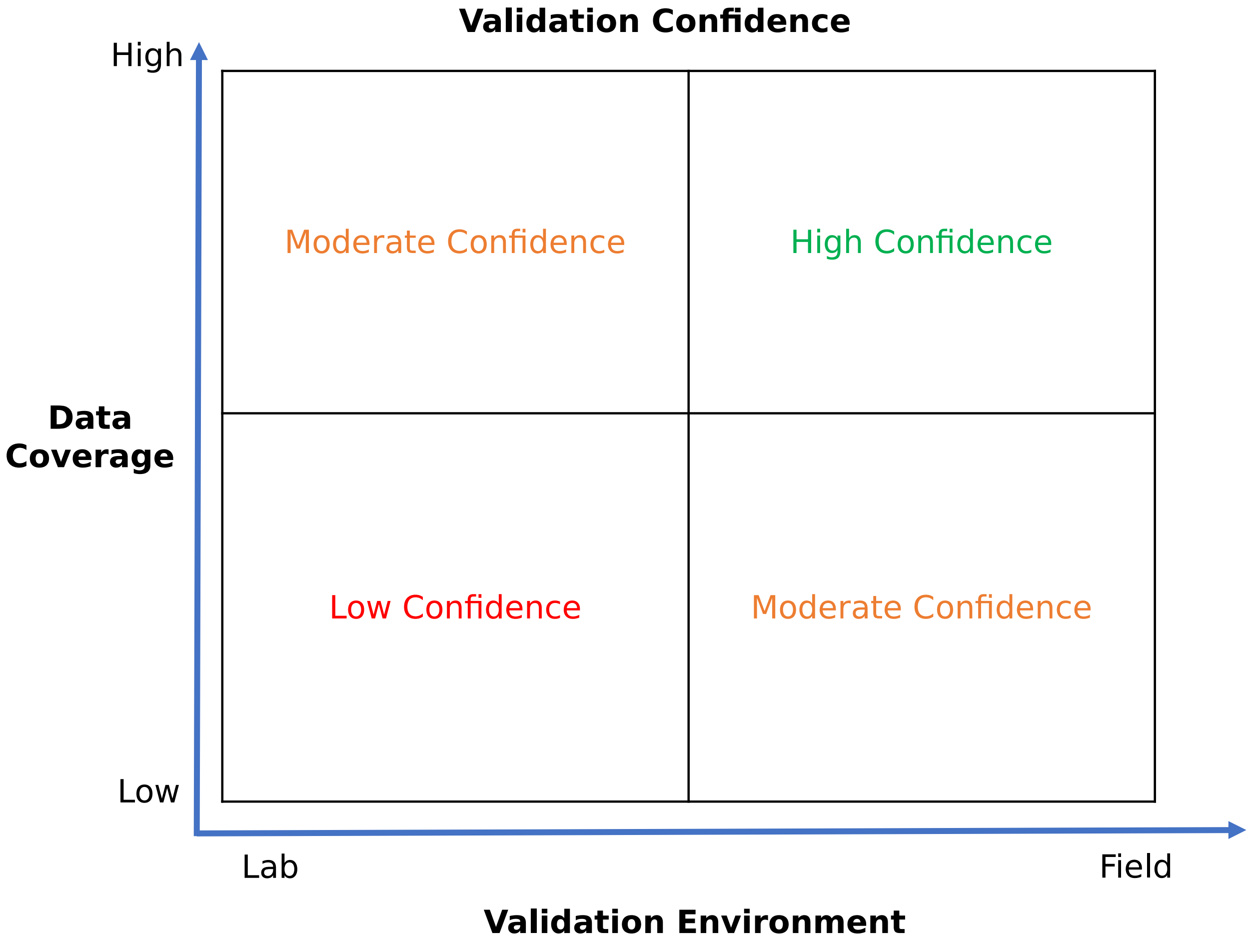

Data Coverage: degree to which the data covers the breadth of configurations, environments, and conditions within the validation scope. For example, high data-coverage for a Lithium Ion battery model would require:

- Data from many different Lithium Ion batteries of different sizes and configurations
- Data for these batteries in various environmental conditions (temperature, pressure, etc.) within the validation scope
- Data for these batteries with various loading profiles within the validation scope
- Data for these batteries with various faults within the validation scope
- etc.

Validation Environment: The environment

Example: Batteries - Chetan

- Battery model development with LaRC team
  - Verification and validation of equivalent ckt and electro-chem models
  - Validation performed on fixed wings* and multi-rotor UAV's – online and offline
- Lab (MACCOR) & Operational Validation
  - Perform characterization tests for operational validation
  - Data from characterization used for model development and verification on lab as well as field data
- Edge work – safety team – approval to fly - at this point a threshold is added
  - Flights tests conducted on autonomous fixed wing UAV*
  - 2-minute warning alarm for 26 flight runs
  - Validation of the SOC algorithm for piloted/autonomous flights.
- Validate RUL estimation with metrics
  - Fig.2 shows plot of **α-λ performance** metric for RUL estimation for a UAV flight profile.

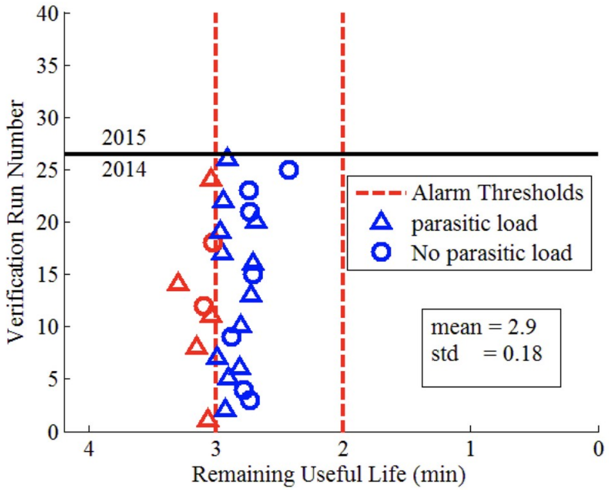

Fig.1. Two-minute alarms for 26 runs

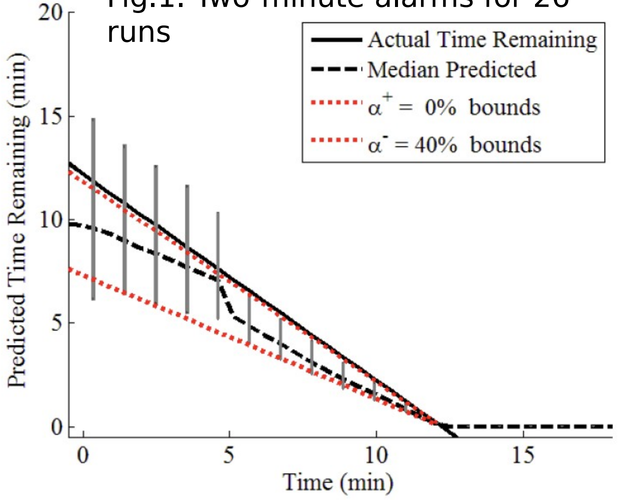

Fig.2. Predicted remaining flying time using α-λ performance metric

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